

Research - Enterprise Security Architecture for Sovereign AI: Defense in Depth Across the Stack

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Enterprise Security Architecture for Sovereign AI: Defense in Depth Across the Stack

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Sovereign AI systems deployed in regulated enterprises require comprehensive security architectures that address threats across the entire technology stack—from physical hardware to application logic. This paper presents a defense-in-depth security architecture for sovereign AI, integrating transport layer security (TLS 1.3, mTLS), data encryption (AES-256-GCM), access control (RBAC/ABAC), identity management (SSO/SAML/LDAP/OIDC), and incident response capabilities. We analyze each layer of the security stack, examining cryptographic protocol selection, key management practices, access control model formalization, and security incident lifecycle management. The architecture implements a zero-trust design where all communication is authenticated and encrypted,

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1. Introduction

The deployment of artificial intelligence systems in regulated enterprises—banking, healthcare, government, critical infrastructure—requires security architectures that protect confidentiality, integrity, and availability across the entire system stack [1]. Unlike consumer AI applications, enterprise sovereign AI systems must defend against sophisticated adversaries including nation-state actors, organized cybercrime, and malicious insiders [2].

Traditional enterprise security architectures have been developed for conventional IT systems (databases, web applications, file servers) and do not adequately address the unique security challenges of AI systems: model extraction attacks, prompt injection, training data poisoning, adversarial inputs, and AI-specific data exfiltration [3]. The security architecture for sovereign AI must integrate conventional enterprise security controls (encryption, access control, identity management) with AI-specific controls (model security, input validation, output monitoring) in a cohesive defense-in-depth framework [4].

This paper presents a comprehensive security architecture for sovereign AI systems organized in a seven-layer defense model:

1. **Physical & Infrastructure Security:** Hardware security modules, TPM, secure enclaves
2. **Network Security:** Segmentation, TLS 1.3, mTLS, firewall rules, data diodes
3. **Cryptographic Security:** AES-256-GCM, key management, certificate management
4. **Identity & Access Management:** SSO/SAML/LDAP/OIDC, RBAC/ABAC, privileged access management
5. **Application Security:** Input validation, output filtering, prompt injection detection, rate limiting
6. **Model Security:** Adversarial robustness, extraction prevention, watermarking, jailbreak detection
7. **Audit & Incident Response:** Continuous monitoring, SIEM integration, incident response procedures, .aioss audit ledger

2. Literature Review

2.1 Enterprise Security Frameworks

Several comprehensive security frameworks guide enterprise security architecture. The NIST Cybersecurity Framework (CSF) provides a risk-based approach organized around five functions: Identify, Protect, Detect, Respond, Recover [5]. NIST SP 800-53 provides a catalog of security and privacy controls for federal information systems [6]. The ISO/IEC 27000 family provides internationally recognized information security management standards [7].

The Zero Trust Architecture (NIST SP 800-207) articulates the principle of never trust, always verify, requiring all access requests to be authenticated and authorized regardless of network location [8]. Zero Trust principles are particularly relevant for sovereign AI systems where models and data may be accessed from diverse internal and external networks [9].

2.2 AI Security Research

AI security has emerged as a distinct research field. The OWASP Top 10 for LLM Applications identifies critical risks including prompt injection, insecure output handling, training data poisoning, supply chain vulnerabilities, and excessive agency [10]. MITRE ATLAS (Adversarial Threat Landscape for Artificial-Intelligence Systems) provides a comprehensive knowledge base of AI-specific attack techniques [11].

Model security research has established several attack categories: - **Model extraction**: Adversaries query a model to reconstruct its architecture or weights [12] - **Model inversion**: Adversaries reconstruct training data from model outputs [13] - **Adversarial examples**: Carefully crafted inputs that cause misclassification [14] - **Backdoor attacks**: Malicious training data that creates hidden behaviors [15] - **Jailbreak attacks**: Prompts designed to bypass safety guardrails [16]

2.3 Cryptographic Standards

Transport Layer Security (TLS) 1.3 (RFC 8446) provides forward-secrecy-protected encrypted communications with reduced handshake latency [17]. Mutual TLS (mTLS) extends TLS with bidirectional certificate authentication, ensuring both client and server are authenticated [18].

AES-256-GCM provides authenticated encryption with associated data (AEAD) using Galois/Counter Mode, combining encryption and integrity verification in a single operation [19]. NIST SP 800-38D specifies the GCM mode of operation [20].

2.4 Identity and Access Management

Security Assertion Markup Language (SAML) 2.0 enables browser-based single sign-on across organizational boundaries [21]. Lightweight Directory Access Protocol (LDAP) provides directory service access for centralized identity management [22]. OpenID Connect (OIDC) extends OAuth 2.0 with identity authentication, providing a modern, REST-based SSO protocol [23].

Role-Based Access Control (RBAC) assigns permissions to roles and users to roles, simplifying permission management in large organizations [24]. Attribute-Based Access Control (ABAC) extends RBAC with dynamic policy evaluation based on subject, resource, action, and environment attributes [25].

3. Technical Analysis

3.1 Transport Security Layer

The transport security layer implements TLS 1.3 with mutual authentication:

Client	Server
ClientHello (supported)	
----->	

```

| ServerHello + Certificate |
|<-----|
| CertificateRequest       |
|<-----|
| ClientCertificate        |
|----->|
| CertificateVerify        |
|----->|
| Finished                 |
|=====>|
| Encrypted Application Data |
|<=====|

```

Configuration: - TLS 1.3 only (no fallback to TLS 1.2) - Cipher suites: TLS_AES_256_GCM_SHA384 (preferred), TLS_CHACHA20_POLY1305_SHA256 - Certificate verification: Full chain validation with CRL/OCSP checking - Client certificates: Required for all API operations (mTLS) - Certificate pinning: Support for HPKP-style pinning for high-security deployments - Session resumption: PSK-based resumption with ticket lifetime of 24 hours [26]

3.2 Data Encryption Layer

Data encryption operates at multiple levels:

At-Rest Encryption: - Filesystem-level: LUKS2 with AES-256-XTS for block device encryption - Database-level: pgTDE (PostgreSQL Transparent Data Encryption) or column-level encryption with pgcrypto - Model storage: Each model artifact is encrypted with a unique data encryption key (DEK) - Backup encryption: Backup archives encrypted with separate backup keys

Key Hierarchy:

Master Key (HSM-protected)

- Storage KEK (Key Encryption Key)
 - Database DEK
 - Model Storage DEKs (per model)
 - Backup DEK
 - Config DEK
- TLS Private Key
- mTLS CA Key
- Audit Signing Key
- TPM Storage Root Key

Keys are managed through a Hardware Security Module (HSM) or TPM-protected key store, with key rotation policies aligned with NIST SP 800-57 [27].

In-Transit Encryption: All network communication uses TLS 1.3 with AES-256-GCM. Internal service-to-service communication (microservice architecture) also uses mTLS with short-lived certificates (24-hour validity) provisioned through SPIFFE/SPIRE for workload identity [28].

3.3 Access Control Architecture

The access control architecture implements a hybrid RBAC/ABAC model:

RBAC Component:

Roles: admin, auditor, operator, developer, user

Permissions (RBAC):

```
admin:      models:*, users:*, audit:*, inference:*
auditor:    audit:read
operator:   models:deploy, models:monitor, inference:*
developer:  models:develop, models:test
user:      inference:chat, inference:embed
```

ABAC Component:

Policies (ABAC):

- Allow inference IF user.department = resource.department
- Allow model:deploy IF user.clearance >= model.classification
- Deny inference IF time.now NOT IN organization.hours
- Allow audit:read IF user.role = auditor AND user.session_mfa = true

Policy evaluation uses the eXtensible Access Control Markup Language (XACML) architecture with a Policy Decision Point (PDP), Policy Enforcement Point (PEP), and Policy Information Point (PIP) [29].

3.4 Identity Provider Integration

The identity layer supports multiple IdP integration patterns:

SAML 2.0: The system acts as a SAML service provider, accepting assertions from enterprise IdPs (Okta, Azure AD, ADFS). SP-initiated SSO with HTTP-POST binding is supported for browser-based authentication [30].

LDAP: Direct LDAP authentication against Active Directory or OpenLDAP for environments without SAML infrastructure. LDAP over TLS (LDAPS) is required. Group membership is synchronized for RBAC role assignment [31].

OIDC: OIDC with authorization code flow and PKCE for modern SSO. Supported providers include Keycloak, Dex, and cloud provider IdPs. ID token claims are mapped to ABAC attributes [32].

3.5 AI-Specific Security Controls

Beyond conventional enterprise security, the architecture implements AI-specific controls:

Prompt Injection Detection: Multi-layer detection using a dedicated classification model, regex patterns, and anomaly detection on embedding similarity. Detected injections trigger graduated responses: warning (low confidence), input rejection (medium confidence), and account suspension (high confidence) [33].

Jailbreak Detection: A specialized classifier trained on known jailbreak patterns (role-play bypass, hypothetical scenarios, token manipulation, encoding obfuscation) with continuous update from threat intelligence feeds [34].

Model Extraction Protection: Rate limiting on inference queries, differential privacy noise on output logits, and detection of systematic querying patterns indicative of extraction attacks [35].

Output Filtering: All model outputs are filtered through a content safety classifier, a PII detection engine (regular expressions + NER), and a policy compliance checker before delivery to the client [36].

3.6 Incident Response Framework

The security incident response framework follows the NIST SP 800-61 lifecycle:

1. **Preparation:** Role definition, playbook development, tooling deployment (SIEM, SOAR), training and exercises
2. **Detection & Analysis:** Security monitoring covers:
 - Authentication anomalies (unusual login times, locations, patterns)
 - API abuse (rate limit violations, unusual parameter patterns)
 - Model behavior drift (unexpected output patterns, quality degradation)
 - Data exfiltration (unusual data volume transfer, unexpected export operations)
3. **Containment, Eradication & Recovery:**
 - Automated containment: API key revocation, user suspension, model isolation
 - Manual intervention: Forensic investigation through .aioss audit ledger
 - Recovery: Verified rollback to known-good state using ledger verification
4. **Post-Incident Activity:**
 - Root cause analysis
 - Security control enhancement
 - Compliance reporting [37]

4. Current State of the Art

4.1 Enterprise AI Security Platforms

Several enterprise AI platforms address security. **NVIDIA Morpheus** provides AI-powered cybersecurity for data center security, including real-time threat detection using GPU-accelerated processing [38]. **HiddenLayer** offers MLDR (Machine Learning Detection and Response) specifically for AI model security, including model scanning and attack detection [39]. **Protect AI** provides security analysis of ML supply chains and model vulnerability scanning [40].

4.2 Compliance Frameworks for AI

AI-specific compliance frameworks are emerging. The **EU AI Act** establishes a risk-based regulatory framework with specific requirements for transparency, documentation, and human oversight [41]. **NIST AI Risk Management Framework** (AI RMF) provides guidance for managing AI risks across the AI lifecycle [42]. **NYDFS Cybersecurity Regulation** for financial services has been interpreted to include AI systems in scope for regulated entities [43].

4.3 Security Standards for ML Infrastructure

The **ML Security Maturity Model** provides a framework for assessing and improving ML security practices [44]. The **Model Card** framework (Mitchell et al.) provides standardized documentation for model transparency and evaluation [45]. The **Datasheets for Datasets** framework provides structured documentation for dataset provenance and characteristics [46].

4.4 Limitations

Current enterprise AI security approaches have several limitations: - Fragmented tooling across security domains (network, access, model security) - Lack of integrated AI incident response playbooks - Insufficient support for air-gapped and disconnected deployment security monitoring - No standardized approach for AI model forensic investigation [47]

5. Relevance to API-OSS

API-OSS implements the complete seven-layer security architecture described above, with tight integration across all layers.

5.1 Security Implementation Status

Layer	Implementation
Physical Security	TPM 2.0 attestation, HSM integration (YubiHSM, SoftHSM)
Network Security	TLS 1.3 only, mTLS required, WireGuard P2P VPN
Cryptographic Security	AES-256-GCM per-field encryption, key rotation pipeline
Identity & Access	SAML/OIDC/LDAP integration, RBAC/ABAC engine
Application Security	Input validation middleware, rate limiting, prompt injection detection
Model Security	Jailbreak detection, extraction prevention, watermarking
Audit & IR	.aioss ledger, SIEM integration (Splunk, ELK), playbook automation

5.2 Integration with Compliance Frameworks

API-OSS maps security controls to multiple compliance frameworks:

Control Domain	SOC 2	HIPAA	FedRAMP	PCI-DSS
Access Control	CC6.1, CC6.2	§164.312(a)(1)	AC-2, AC-3	7.1, 7.2
Encryption	CC6.7	§164.312(e)(2)(ii)	SC-8, SC-13	4.1
Audit Logging	CC5.2	§164.312(b)	AU-2, AU-3	10.2, 10.3
Incident Response	CC7.3, CC7.4	§164.308(a)(6)	IR-4, IR-5	12.10
Backup/Recovery	CC7.5	§164.308(a)(7)	CP-9, CP-10	12.3

5.3 Audit Ledger Forensics

The .aioss audit ledger provides tamper-evident forensic capabilities. During incident response, investigators can: - Trace all actions taken by a compromised account across the entire system - Verify that logs have not been tampered with through hash chain verification - Identify the exact

model version and configuration used for any inference - Determine the data that was accessed, by whom, and through which tools [48]

5.4 Security Automation

API-OSS implements automated security responses through its event system: - Automatic API key revocation when anomalous usage patterns are detected - Model isolation when drift in output quality or safety category is detected - User notification for suspicious login attempts - Automated compliance report generation for quarterly audits [49]

6. Future Directions

Confidential AI: Extending trust boundaries with confidential computing (AMD SEV-SNP, Intel TDX, NVIDIA Confidential Computing) to protect model weights and inference data from the host operating system [50].

Federated Security Operations: Developing protocols for sharing security telemetry across sovereign AI deployments without revealing sensitive data, enabling collective threat detection through federated learning on security events [51].

AI-Guided Incident Response: Using AI to accelerate incident response by automatically correlating security events, generating forensic hypotheses, and recommending containment actions through a security-specific AI agent [52].

Post-Quantum Cryptography Migration: Planning migration to post-quantum cryptographic algorithms (CRYSTALS-Kyber, CRYSTALS-Dilithium, SPHINCS+) as quantum computing advances threaten current public-key infrastructure [53].

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